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Adverse events in surgical inpatients: A comparative analysis of public hospitals in Victoria

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Abstract

We compare adverse event rates for surgical inpatients across 36 public hospitals in the state of Victoria, Australia, conditioning on differences in patient complexity across hospitals. We estimate separate models for elective and emergency patients which stay at least one night in hospitals, using fixed effects complementary log-log models to estimate AEs as a function of patient and episode characteristics, and hospital effects. We use 4 years of patient level administrative hospital data (2002/03 to 2005/06), and estimate separate models for each year. Averaged over four years, we find that adverse event rates are 12% for elective surgical inpatients, and 12.5% for emergency surgical inpatients. Most teaching hospitals have surprisingly low adverse event rates, at least after adjusting for the higher medical complexity of their patients. Some larger regional hospitals have high adverse events rates, in particular after adjusting for the below average complexity of their patients. Also, some suburban hospitals have high rates, especially the ones located in areas of low socioeconomic profile. We speculate that high rates may be due to factors beyond the control of the hospitals, such as staff shortages. We conclude that at present, care should be taken when using adverse event rates as indicators of hospital quality.

Keywords: adverse events, hospital performance, hospital quality, patient complexity

JEL Classification: I11, D21, C2, H4, L3

Introduction

It is estimated that adverse events (AE) during hospital admission affect nearly one out of 10 patients (de Vries, Ramrattan et al. 2008). An AE is usually defined as an unintended injury or complication resulting in prolonged hospital stay, disability at the time of discharge or death and caused by healthcare management rather than by the patient's underlying disease process (Wilson, Runciman et al. 1995; Thomas, Studdert et al. 2000). AE are now widely agreed to be a serious problem, annually killing more people than motor vehicle accidents, breast cancer, and AIDS. This makes AE the fifth leading cause of death in the USA (Kohn, Corrigan et al. 2000). Thus, prevention of AE promises significant societal benefits.

In recent years, the focus in thinking about AEs has shifted from the person approach—blaming individuals for errors—to the systems approach (de Vries, Ramrattan et al. 2008). The systems approach assumes that people will make mistakes, and that the system that surrounds them should provide a safety net for these mistakes. Therefore, efforts to eliminate AEs should be directed towards a particular system, i.e. hospital or hospital department (Dankelman and Grimbergen 2005). In practice, these efforts aim to reduce the complexity of providing medical care, by -for example- standardization of procedures and medical equipment, checklists, quality testing of medical equipment, and staff training. Both the implementation and ongoing upkeep of such measures are associated with costs to the hospital, because they require investments in equipment and additional staff time. Thus, efforts aimed at improving hospital quality should only be implemented when significant benefits can be expected, and they should be targeted towards hospitals with the greatest potential for reductions in AE. To this end, it is necessary to gain a more detailed understanding of AE, in particular which hospitals experience highest rates of AE. This will help hospital managers and politicians to work towards elimination of AE on hospital level and target efforts to hospitals with greatest need for improvement.

The purpose of this paper is to estimate adverse event rates for surgical inpatients in 36 public hospitals in the state of Victoria, Australia, conditional on observable differences in patient complexity across hospitals. We estimate separate models for elective and emergency patients which stay at least one night in hospitals, using fixed effects complementary log-log models to model AEs as a function of patient and episode characteristics, and hospital effects (dummies). We use 4 years of patient level administrative hospital data (2002/03 to 2005/06), and estimate separate models for each year.

Methods

For the purpose of analysis we assume that adverse events may arise for four main reasons: patient explanatory factors (such as comorbidities and age), hospital level explanatory factors (such as teaching status, staffing levels or size), unobservable factors on hospital level (hospital effects), and unobservable factors on patient level (interpreted as random chance). The economic literature on hospital performance interprets hospital effects often as 'managerial effort' or policies and regulations affecting a particular hospital (Jacobs, Smith et al. 2006). This interpretation of hospital effects relies on the assumption that other sources of variation, most notably systematic variation in patients' medical complexity across hospitals, are sufficiently taken account of in the analysis. If hospital effects represent managerial effort, this implies that variations in AE rates across hospitals which remain after taking account of differences in observable factors and random chance give an indication of the extent to which AEs may be amenable to interventions by the hospitals (Hauck, Rice et al. 2003; Jacobs, Smith et al. 2006; Smith and Street 2006).

It also implies that a certain portion of AEs which are attributable to unobservable factors on hospital level can be considered preventable. Our analysis cannot inform how high this proportion is. However, if a hospital has significantly higher/lower AE rates than average in all four years (conditional on observable factors), we interpret this as evidence that factors on hospital level contribute to these high/low rates of AEs. Some of these factors, such as poor safety procedures, may be amenable to the actions of hospital management. Thus, hospitals with above average AE rates in all four years may have shortcomings in their management, and may attract further enquiry and detailed investigation, and possibly implementation of procedures to prevent AEs in future. Hospitals with below average AE rates, on the other hand, seem to do well and policy makers may want to identify the reasons for low AE rates, and possibly learn more about their successful management strategies.

Modelling adverse events is fraught with various methodological problems, some of which we address in this paper. First, AEs are infrequent events. The (unadjusted) rate of AEs varies between 16.8% and 17.8% for elective, and 15.7% and 18.6% for emergency inpatient episodes over the observation period *(Tables 2* and *3).* We use asymmetric complementary log-log models, which are usually recommended for binary dependent variable models with unequal distribution of zeroes and ones, in our situation excess zeroes (Cameron and Trivedi 2005). A second problem arises due to clustering effects with respect to hospitals, i.e. patients in the same hospitals are more alike than patients in different hospitals. One patient having an AE is likely to increase the probability of another patient in the same hospital (or hospital department) having an AE. This is because system failures and insufficient safety measures affect many or all procedures undertaken in the hospital, infections may spread across patients, or faulty medical devices may be used for several procedures. In rare instances, the incompetence of one doctor may lead to AEs in several of his patients. We take account of clustering with hospital specific fixed effects.

Suppose the propensity of suffering an adverse event for the *i*-th episode is given by the latent equation:

$$AE_i^* = \beta_0 + X_i\beta_X + H_i\beta_H + \varepsilon_i, \tag{1}$$

with $AE_i^* > 0$ mapped to $AE_i = 1$ if patient *i* suffered at least one adverse event and $AE_i^* \leq 0$ to $AE_i = 0$ if not, where X_i is a vector of covariates representing patient observable characteristics, and H_i is a vector of hospital dummies, all $\beta's$ are coefficients to be estimated, and ε_i is the error term which is assumed to follow the extreme value (or log-Weibull) distribution. The coefficient vector β_H measures the marginal effects of individual hospitals on the propensity of AEs that are not attributable to observable patient risk factors. They can be used to quantify the hospital fixed effects and compare hospitals with respect to the probability of AEs. We estimate separate models for elective and emergency inpatients, and for each of the 4 years.

Data

We use the Victorian Admitted Episodes Data (VAED) for surgical inpatients in public hospitals in the state of Victoria, Australia, for four years from 2002/03 to 2005/06. The VAED are administrative hospital data of high quality as hospitals have a strong financial incentive to generate detailed records of all their patients because they receive the largest part of their budget via casemix funding. Our sample consists of 36 hospitals with over 72,000 inpatient elective episodes, and over 41,000 inpatient emergency episodes in each year (see tables 2 and 3). One hospital does not report AEs in any of the years. Each episode starts with a patient's admission to a hospital department and ends with her discharge from that department. We exclude dialysis, radiology, chemotherapy, and dental episodes, and we exclude patients under 18 years of age. Hospital dummies are included for all hospitals which report more than 2000 surgical episodes in at least three of the four years. All other hospitals make up the reference (base) category. We cannot estimate fixed effects for those reference hospitals, but they would be problematic to interpret anyway because reference hospitals are small regional hospitals which only perform simple procedures associated with few AEs. We limit our sample to surgical inpatients, i.e. patients staying at least one night, in surgical 'Disease Resource Groups'. Modelling AEs for medical patients is complicated by the fact that their length of stay in hospital may impact on the probability of suffering AEs (Hauck and Zhao 2010).

Table 1 provides definitions of all variables, and *tables 2* and *3* summary statistics for elective and emergency inpatients, respectively. The dependent variable 'AE' indicates whether the patient experienced one or several AEs during admission. We code 'AE' as a binary variable because different AEs during one episode may not be independent events. For example, a patient may suffer both hemorrhaging and an infection due to one mistake during surgery. Recording two or more AEs per episode would overstate the number of mistakes happening in hospitals. Victorian hospitals record AEs arising during the episode. These so-called 'complicating conditions' are not present at the time of the admission (or when the episode of care commenced), and they are "conditions resulting from misadventure during surgical or medical care in the current episode of care, or an abnormal reaction to, or later complication of, surgical or medical care occurring during the current episode of care" (Department of Health 2005). A previously existing condition that was not diagnosed until after the episode of care started is not an AE, but an associated condition or the primary diagnosis if it is the reason for admission; see Ehsani et al. (2006) for a more detailed analysis of the types and incidences of AEs in Victorian hospitals.

Most explanatory variables describe characteristics of the patient, in particular medical complexity, and characteristics of the surgical episode. Severity grades are based on reported diagnoses and treatments. Patients who have multiple stays in hospital in the financial year, are subjected to a larger number of procedures, are transferred or die at the end of the episode are likely to be more complex. It has been shown that emergency surgical patients admitted on a weekend or a public holiday experience higher rates of AEs (Bell and Redelmeier 2001; Gogel, Liron et al. 2002; Arias, Taylor et al. 2004; Cram, Hillis et al. 2004; Becker 2007; Fonarow, Abraham et al. 2008; Schwierz, Augurzky et al. 2009). This may be due to delays in treatment because of staff shortages, or surgeries undertaken by inexperienced medical staff. Patient level indicators of medical need are ‘age’, ‘obesity’, ‘seifa’ as an indicator of social advantage on small area level, and ‘private’ showing whether a patient payed privately for the stay in hospital. In Australia, a large part of private payments are reimbursed by private health insurance, the uptake of which is linked to income. We include two interactions terms *(age*number of procedures* and *age*multiple stays)* in all models. We further adjust for patients’ medical complexity by including separately all comorbidities comprised in the Charlson index (Charlson, Pompei et al. 1987). A patient is classified as suffering one or more of these comorbidities based on recorded diagnoses codes. To guarantee anonymity of the hospitals in our study we do not disclose their names. However, for interpretation of the results, we do classify hospitals into six types according to their geographical location, teaching status and whether they are specialized on certain types of procedures.

Results and Discussion

Tables 4 and *5* show marginal effects (ME) and average effects (AvE) of the explanatory variables for elective and emergency inpatients, respectively, *figures 1-4* and *5-8* display AE rates for elective and emergency inpatients for all hospitals, conditional on other explanatory factors, *figure 9* displays conditional AE rates for elective inpatients for all years and for hospitals which significantly diverge from average rates in all four years, and *figure 10* displays AE rates for elective inpatients for all years, unadjusted for other explanatory factors.

Average and Marginal Effects

AvE and ME are evaluated at the means of the other explanatory variables. Most effects are as expected. Age, number of procedures, high medical severity grading 3, and experiencing multiple hospital stays in a year all significantly increase risk of AEs, both for elective and emergency patients. Being transferred is associated with increased risk of AEs for elective patients, but decreased risk for emergency patients. This divergence could be explained by differences in the underlying reasons for transfers between these two patient groups. Elective patients may be transferred at the end of their stay, for example to rehabilitation, whereas complex emergency patients are transferred early on, for example to a teaching hospital. If this is the case, AEs for elective patients are more likely to be reported in the original hospital, whereas AEs for emergency patients are reported in the destination hospital.

Paying privately decreases risk for elective patients (although the effect is only statistically significant in 2004/05), but increases risk for emergency patients (statistically significant only in the last two years). Paying privately reduces waiting times for both patient groups. Private paying elective patients are likely to have a higher socioeconomic profile, and may therefore constitute a patient group of lower medical need and thus lower risk for AEs. Private paying emergency patients, on the other hand, may have an inelastic demand for medical care because they have acute health problems and thus a high willingness to pay for prompt medical treatment irrespective of income. Social advantage, gender, private payment, obesity, weekend admission, or whether the patient died in hospital have no significant effects on AE rates. It is not surprising that comparably large effects are estimated for medical severity grading 3 with an increase in probability of around 10% for elective patients, and between 3.6% and 6.4% for emergency patients. Elective and emergency patients with multiple stays in hospital in a year experience between 3.5% and 5.9% higher probability of AEs.

Comorbidities which significantly increase risk of complications in particular for emergency patients are cerebrovascular event, acute myocardial infarction, peripheral vascular disease, cancer, chronic obstructive pulmonary disease, and peptic ulcer. In some years, patients with one or several of these comorbidities experience an up to 11% greater risk of AEs. Chronic heart failure is mainly a risk factor for elective surgical patients. Surprisingly, suffering from diabetes, metastatic cancer or hemiplegia/paraplegia (emergency patients only) significantly decreases probability of AEs, in comparison to not suffering from those comorbidities. Possibly, patients with these comorbidities are subjected to less complex and invasive procedures than comparable patients without them. This in turn may decrease the risk of AEs for patients with these particular comorbidities.

Hospital Fixed Effects

Figures 1-4 show AEs rates by hospital for elective surgical inpatients by year, and *figures 5-8* show AE rates for emergency surgical inpatients, conditional on other explanatory factors. The figures indicate the type of hospital (sub: suburban; teach: teaching; reg: regional, spec: specialty). The horizontal axes mark the predicted (average) rates of AEs across the whole sample, which increase from 11.1% to 13.0% over the years for elective episodes and vary between 10.2% and 12.8% for emergency episodes. Hospitals with an estimated 95% confidence interval which overlaps the axes do not diverge significantly from the average rate of AEs, and hospitals with a confidence interval above/below the axes have significantly higher/lower AE rates than the average, conditional on explanatory factors. It is notable that for both elective and emergency patients, most hospitals lie above the overall predicted rate of AEs for all hospitals in Victoria. Hospitals in the reference category perform only few operations per year, and these are probably simple procedures associated with few complications. This may explain why most of the larger hospitals for which we calculate fixed effects lie above the predicted rate.

AE rates vary quite strongly across hospitals for elective inpatients, but less for emergency inpatients (in the following discussion, numbers for 2005/06 are presented in the text and numbers for 2002/03, 2003/04, 2004/05 in brackets). For only 7 (6, 4, 6) hospitals, estimates for elective AE rates are not significantly different from average rates; for all other hospitals, they are different. Emergency rates, however, are insignificant for more than half of the sample (21 hospitals) in the last three years (03/04: 20; 04/05 and 05/06: 21), and 13 hospitals in 2002/03. This may partly be explained by the lower number of observations for emergency episodes, which in turn leads to larger confidence intervals. For elective inpatients, 6 (4, 5, 3) hospitals lie below average AE rates, and 5 (6, 7, 9) hospitals lie below for emergency episodes. For elective inpatients, 15 (9, 11, 11) hospitals have point estimates of AE rates below 20%, but they are still significantly above average. For emergency inpatients, 7 (4, 4, 14) hospitals lie below 20%, but still above average. For elective inpatients, 7 (17, 15, 13) hospitals have point estimates above 20%, and 2 (3, 3, 0) even above 30%, and 2 (1, 4, 0) hospitals lie above 20% for emergency inpatients.

Hospitals with above average AE rates in elective procedures tend also to have above average rates in emergency procedures. For example, hospitals dum16 and dum19 (teaching hospitals), and dum33 (a large regional hospital) are among the hospitals with highest AE rates for both groups of patients, in nearly each year. Hospitals dum7, dum10, dum12 and dum34 (suburban/city hospitals), and dum24 and dum25 (large regional hospitals) are above average in most years, for both elective and surgery procedures. Hospitals dum20 and dum23 (large regional hospitals) are above average for elective, but not emergency procedures. Hospital dum6 (a teaching and specialized hospital) is the only one with below average AE rates in all years for both elective and emergency procedures. Hospitals dum18, dum26, dum35 and dum35 are below average in some years.

Figure 9 shows AE rates for hospitals which lie significantly above or below predicted AE rates in all four years. Hospitals which do not diverge significantly from average in at least one of the four years, or which lie below average in one, but above average in other years, are not charted in *figure 9.* All rates are adjusted for explanatory factors, including patients' complexity, according to model (1). A surprisingly large number, 21 out of 35 hospitals, differ from average AE rates in all years. Of those, three regional (dum7, dum27, dum33), two teaching (dum3, dum16), and one suburban hospital (dum10) have AE rates at or above 20% in all four years. These rates are adjusted for patients' characteristics, and a comparison with unadjusted AE rates is revealing (see *figure 10).* AE rates in *figure 10* are not adjusted for patients' medical complexity or other explanatory factors. Thus, it is not surprising that teaching hospitals report highest and above average AE rates, as they treat the most complex cases. In fact, for most hospitals, unadjusted AE rates are higher than adjusted ones. This implies that patient characteristics, in particular comorbidities, explain at least a certain portion of the observed AEs. The relatively marked differences in adjusted and unadjusted rates also imply that the explanatory variables in our model are relatively good predictors of AEs.

Focusing on the hospitals with high adjusted AE rates, we find that the two teaching hospitals (dum3 and dum16) have even *higher* unadjusted AE rates. This implies that high AE rates in those two hospitals are at least partly attributable to the fact that they treat patients of above average medical complexity. This pattern can also be observed for other teaching hospitals (dum3, dum8, dum9, dum19). The suburban hospital dum10 has similar AE rates whether they are adjusted for patient complexity or not. This implies that hospital dum10 treats patients of average medical complexity and the high AE rates in this hospital cannot be attributed to observed patient characteristics. Interestingly, all three regional hospitals dum7, dum27 and dum33 with high adjusted AE rates have *lower* unadjusted AE rates. This pattern can also be observed for a few other regional hospitals (dum23, dum24, dum25). It implies that (a) those hospitals treat patients of comparably low medical complexity, and (b) unobservable factors not included in our model are most likely causing high AE rates in regional hospitals.

Conclusion

We use estimated average effects on hospital fixed effects in a binary variable model of AEs to make inference on the influence of hospitals on AEs, conditional on observable patient level risk factors. Averaged over four years, we find that AE rates are 12% for elective surgical inpatients, and 12.5% for emergency surgical inpatients. Across the years, quite a large number of hospitals show little changes in their AE rates for elective, but greater ones for emergency episodes. The majority of teaching hospitals have surprisingly low AE rates, at least after adjusting for the higher medical complexity of their patients. Large regional hospitals have high AE rates, in particular after adjusting for the below average complexity of their patients. Also, some suburban hospitals have high AE rates, especially the ones located in areas of low socioeconomic profile.

Of course, and as we discuss below, hospitals may differ from average AE rates for many reasons other than managerial competence (Hauck, Rice et al. 2003). However, the working hypothesis is that if a hospital shows comparably large and statistically significant divergences from average in all four years, there is strong prima facie evidence that some unobserved factors on hospital level cause these large divergences. Once patient characteristics have been controlled for, large variations indicate substantial disparities across hospitals in AE rates. We infer that these disparities are, at least in part, due to managerial accomplishment. For example, unobserved managerial actions might influence the introduction and proper execution of safety checks and other measures on system level which prevent the occurrence of AE. With this interpretation, we follow the economic literature on organizational performance assessment. Estimated average effects are interpreted as managerial effort on hospital level, and divergences from average (predicted) rates of complications as below/above average performance.

There have been proposals in the health economics literature to link incentive payments to observed performance on AEs (see McNair et al (2009), and Iezzoni (2009) for a critical discussion). Our results indicate that care should be taken when interpreting fixed effects as indicators of performance, and even more so when linking payments to estimated AE rates. First, adjustments for casemix complexity may be inadequate because of unobservable differences in patients' medical complexity. Hospitals in Victoria and other countries with casemix payment systems have sophisticated reporting systems and they are usually very diligent in reporting patients' complexity because their reimbursement relies on accurate reporting. They allocate each patient to one of hundreds of different disease resource groups (DRGs) which attract set amounts of payments from the government. However, it has been shown that there are still differences in patients' complexity within DRGs which cannot be captured by the records (Olsen and Street 2008; Laudicella, Olsen et al. 2009). If these differences vary systematically across hospitals, some hospitals could have higher AE rates simply because they tend to treat more complex patients within each DRG. Holding them accountable for above average AE rates would be unreasonable as they are, at least partly, due to causes beyond their control. This could be a possible reason for higher adjusted AE rates in teaching hospitals. In our sample of Victorian hospitals, however, there is only one teaching hospitals with very high adjusted AE rates, whereas others have average or even lower than average AE rates. This is an indication that our risk adjustment may be adequate, and that very high AE rates in one teaching hospital may indeed be due to poor performance.

However, there is a second reason why care should be taken when interpreting fixed effects as indicators of performance. Hospitals may vary in their diligence of reporting AEs. In principle, hospitals have a strong financial incentive to report AEs, because it may allocate patients to a DRG category which attracts higher reimbursement. However, this does not apply to all AEs. In addition, our analysis is limited to 'C-prefixed' complications and thus relies on hospitals attaching the prefix to complications which arise during admission. Some hospitals may be more diligent than others in distinguishing hospital acquired from community acquired complications. For example, two hospitals (dum32 and dum36) do not report any AEs in all or some years, and a very low number in other years, which is likely due the fact that they systematically understate C-prefixed AEs in their patient records. If all hospitals would misreport in a similar or random fashion, this would not be such a problem. It is quite likely, though, that misreporting is not random, which makes it important to interpret estimated AE rates with care, and investigate the reasons for very low or very high reported AE rates.

Another reason why it is problematic to link payments to estimated performance is the fact that some causes for AEs on hospital level are most likely beyond the control of the hospital management. We find that large regional hospitals in rural areas have high AE rates, in particular after taking account of their comparably low casemix complexity. It is difficult to attract medical staff to work in rural areas, so poor performance may be due to underqualified and overworked doctors and nurses. Also, there is anecdotal evidence that doctors are forced to undertake emergency procedures for patients which require immediate care and/or are too instable to be transported to a teaching hospital in Melbourne. Those procedures may be associated with higher risk of AEs, but save lives in certain situations. Cutting funding for hospitals operating under difficult conditions would be counterproductive and may result in even higher AE rates. Instead, policy makers should look at ways of alleviating the pressure these hospitals are operating under to guarantee a high level of care for the rural population of Victoria.

Some suburban hospitals have high AE rates, in particular the ones located in areas of low socioeconomic profile. Patients in those hospitals are likely to be of lower socioeconomic profile and have greater medical needs, and attracting staff to work in those hospitals may be difficult. Again, cutting funding for these hospitals may be counterproductive. Instead, policy makers may want to consider encouraging different suburban hospitals to each specialize on a limited range of procedures. This may imply slightly higher travel costs for patients, because a particular procedure may not be offered by their local hospital but by one in a neighbouring suburb. However, specialization would allow hospitals to standardize procedures, to acquire specialized equipment and to target staff training more effectively. Greater standardization of procedures has been shown to help reduce AE rates in hospitals (Dankelman and Grimbergen 2005).

Our analysis cannot inform on the reasons why some hospitals have above or below average AE rates. However, we find surprising consistency in differences between unadjusted to adjusted AE rates across years, and for different types of hospitals. Teaching hospitals tend to have lower adjusted than unadjusted AE rates, whereas regional hospitals have higher adjusted than unadjusted AE rates, consistently across all four years for most hospitals. High AE rates in teaching hospitals seem partly explained by their above average patients' medical complexity, whereas large regional hospitals seem to treat patients of below average complexity. Comparing regional hospitals with all other hospitals in the sample, AE rates of regional hospitals should really be lower, considering that they treat relatively straightforward medical cases. This is an indication that to a larger extent than in other hospitals, unobservable factors on hospital level seem to be responsible for high AE rates in regional hospitals. We can only speculate what these factors are, but staff shortages and insufficient capacity to undertake complex emergency procedures may be some of them. These factors would be largely beyond the control of hospitals managers, but the responsibility of state and commonwealth government. Therefore, we conclude that using AE rates as indicators of performance, or even linking performance payments to AE rates, may not be warranted at this point in time. On the contrary, such measures could be counterproductive and aggravate the problem, in particular in regional or certain suburban hospitals operating under difficult conditions. Instead, high estimated AE rates should lead to further investigation of the affected hospitals, and a constructive search for ways to help them reduce AEs on all levels of government. Our results support policy makers in targeting system level approaches for the reduction of AEs to public hospitals in Victoria which most need their support.

Table 1: Variables definitions

AE	α has at least one adverse event
Episode characteristics	
number of procedures	number of treatments and interventions
severity grade 1	α is classified low medical complexity
severity grade 2	α is classified medium medical complexity
severity grade 3	α is classified high medical complexity
multiple stays	α has more than one hospital stay in this financial year
weekend admission	α is admitted on a Saturday, Sunday or public holiday
home	α is discharged home
death	α dies in hospital
transfer	α is transferred to another hospital or hospital department
Patient characteristics	
age	age of patient
seifa	Index of social dis-/advantage, based on postcode of patient
female	sex of patient
obese	α is classified as obese
private	α paid privately for the episode
Charlson comorbidites	
ami	α has acute myocardial infarction
chf	α has congestive heart failure
pvd	α has peripheral vascular disease
cva	α has a cerebrovascular event
dementia	α has dementia
copd	α has chronic obstructive pulmonary disease
ctd	α has connective tissue disease
pud	α has peptic ulcer
ld	α has mild liver disease
diab	α has diabetes
hp papl	α has hemiplegia or paraplegia
renaldis	α has renal disease
cancer	α has cancer
meta cancer	α has metastatic cancer
severe ld	α has severe liver disease
hiv	α is HIV positive or has AIDS
Hospital characteristics	
teachosp	α is treated in a teaching hospital
spec hosp	α is treated in a specialized hospital
city hosp	α is treated in a city or suburban hospital
regional hosp	α is treated in a large regional hospital
smallregional hosp	α is treated in a small regional hospital
other hosp	α is treated in any other hospital

α = Dichotomous variable that equals 1 if patient

Table 2: Summary statistics for elective inpatients
(reported are percentages for binary variables, and means and standard errors for continuous variables)

	year 0203		year 0304		year 0405		year 0506	
Number of episodes	72,958		4,404		4,941		87,790	
	mean or %	SE	mean or %	SE	mean or %	SE	mean or %	SE
AEs	16.8%		17.2%		17.8%		17.8%	
Episode characteristics								
numberop	3.2	1.3	3.3	1.2	3.3	1.2	3.4	1.2
severity 1	25.6%		24.9%		25.5%		25.3%	
severity 2	45.2%		46.4%		45.7%		46.1%	
severity 3	29.2%		28.7%		28.8%		28.5%	
multiple-stay	36.6%		34.9%		33.8%		34.9%	
weekendadmin	3.4%		2.9%		3.1%		3.4%	
homesep	94.1%		95.0%		94.8%		94.8%	
death	0.9%		0.4%		0.4%		0.3%	
transep	4.9%		4.6%		4.8%		4.9%	
Patient characteristics								
age	50.6	22.8	50.1	22.6	50.2	22.5	50.4	22.4
seifa	984.8	73.2	982	72.0	982	71.1	983	71.2
female	52.5%		52.5%		52.5%		52.4%	
obese	0.8%		0.8%		0.9%		1.1%	
private	10.1%		10.1%		10.4%		9.9%	
Charlson comorbidites								
ami	0.7%		0.6%		0.8%		0.7%	
chf	0.8%		0.6%		0.6%		0.5%	
pvd	0.7%		0.7%		0.7%		0.7%	
cva	1.1%		0.9%		0.9%		0.8%	
dementia	0.1%		0.1%		0.1%		0.1%	
copd	0.9%		0.7%		0.7%		0.7%	
ctd	0.1%		0.1%		0.0%		0.1%	
pud	0.1%		0.1%		0.1%		0.1%	
ld	0.1%		0.1%		0.1%		0.2%	
diab	4.7%		4.9%		2.4%		2.0%	
parap	0.3%		0.2%		0.2%		0.2%	
renaldis	17.0%		17.5%		17.3%		17.2%	
cancer	11.5%		10.9%		11.0%		11.0%	
meta_cancer	3.7%		3.2%		3.3%		3.5%	
severe_ld	0.0%		0.0%		0.0%		0.0%	
hiv	0.1%		0.0%		0.1%		0.0%	
Hospital characteristics								
teachosp	29.7%		27.2%		27.1%		26.5%	
spechosp	7.7%		8.8%		8.4%		8.0%	
cityhosp	26.2%		29.7%		29.9%		30.8%	
regionalhosp	24.7%		24.4%		25.0%		24.0%	
smallregio~p	10.4%		9.8%		8.5%		8.2%	
otherhosp	1.2%		0.1%		1.1%		2.6%	

Table 3: Summary statistics for emergency inpatients
(reported are percentages for binary variables, and means and standard errors for continuous variables)

	year 0203		year 0304		year 0405		year 0506	
Number of episodes	44,380		41,475		42,600		43,771	
	mean or %	SE	mean or %	SE	mean or %	SE	mean or %	SE
AEs	15.7%		18.6%		17.8%		16.7%	
Episode characteristics								
numberop	3.1	1.8	3.8	1.3	3.8	1.3	3.8	1.3
severity1	23.6%		19.3%		19.3%		19.2%	
severity 2	41.5%		41.7%		42.1%		42.1%	
severity3	34.8%		39.0%		38.5%		38.7%	
multiple-stay	35.9%		35.3%		35.2%		35.9%	
weekendadmin	28.6%		28.8%		28.8%		28.9%	
homesep	81.0%		79.9%		80.1%		80.3%	
death	3.3%		3.3%		3.2%		3.2%	
transep	15.4%		16.8%		16.8%		16.6%	
Patient characteristics								
age	51.1	25.3	50.0	24.9	49.7	24.7	50.1	24.8
seifa	997.0	79.2	996	77.9	996	78.0	997	77.9
female	46.4%		44.9%		44.6%		45.1%	
obese	0.5%		0.4%		0.4%		0.4%	
private	6.9%		9.0%		9.7%		9.9%	
Charlson comorbidites								
ami	4.6%		5.9%		6.1%		6.8%	
chf	3.2%		2.3%		2.0%		2.1%	
pvd	0.9%		1.1%		1.0%		1.0%	
cva	2.6%		1.9%		1.9%		1.9%	
dementia	0.2%		0.1%		0.1%		0.2%	
copd	3.4%		1.3%		1.3%		1.3%	
ctd	0.1%		0.1%		0.1%		0.1%	
pud	0.6%		0.6%		0.6%		0.6%	
ld	0.3%		0.2%		0.2%		0.3%	
diab	3.7%		3.1%		1.4%		1.3%	
parap	1.0%		0.7%		0.6%		0.8%	
renaldis	10.6%		10.2%		10.1%		10.0%	
cancer	5.5%		5.1%		5.0%		5.1%	
meta_cancer	2.8%		2.5%		2.5%		2.5%	
severe_ld	0.2%		0.1%		0.1%		0.2%	
hiv	0.0%		0.0%		0.0%		0.0%	
Hospital characteristics								
teachosp	32.7%		37.2%		36.9%		37.8%	
spechosp	2.7%		3.2%		3.2%		3.1%	
cityhosp	37.0%		35.8%		36.4%		35.5%	
regionalhosp	21.4%		21.8%		21.9%		21.8%	
smallregio~p	6.2%		1.9%		1.6%		1.6%	
otherhosp	0.0%		0.0%		0.0%		0.2%	

Table 4: Average and marginal effects, elective inpatients, all years^

	year 0203		year 0304		year 0405		year 0506	
predicted prob	0.111		0.116		0.126		0.130	
variable	dy/dx	P>|z|	dy/dx	P>|z|	dy/dx	P>|z|	dy/dx	P>|z|
lnage	0.034	0.000	0.029	0.000	0.027	0.000	0.027	0.000
seifa	0.000	0.128	0.000	0.023	0.000	0.923	0.000	0.231
severi~1*	-0.012	0.000	-0.025	0.000	-0.033	0.000	-0.032	0.000
severi~3*	0.089	0.000	0.099	0.000	0.102	0.000	0.109	0.000
female*	0.002	0.341	0.000	0.960	-0.001	0.468	0.001	0.632
private*	-0.005	0.148	-0.006	0.086	-0.008	0.024	-0.004	0.245
multip~y*	0.042	0.000	0.044	0.000	0.038	0.000	0.035	0.000
obese*	0.005	0.660	-0.009	0.354	-0.015	0.135	-0.035	0.000
weeken~n*	-0.002	0.673	-0.002	0.686	-0.006	0.247	-0.022	0.000
death*	0.011	0.277	-0.012	0.192	0.011	0.367	0.004	0.751
transep*	0.024	0.000	0.017	0.000	0.021	0.000	0.020	0.000
numberop	0.038	0.000	0.036	0.000	0.038	0.000	0.044	0.000
ageop	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
agemulti	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
ami*	0.064	0.000	0.074	0.000	0.062	0.000	0.070	0.000
chf*	0.049	0.000	0.052	0.000	0.055	0.000	0.059	0.000
pvd*	0.020	0.022	0.043	0.000	0.031	0.001	0.033	0.001
cva*	0.022	0.007	0.026	0.001	0.011	0.197	0.026	0.006
dementia*	0.009	0.800	-0.019	0.475	-0.011	0.695	-0.016	0.641
copd*	0.022	0.048	0.027	0.011	0.036	0.002	0.033	0.004
ctd*	-0.041	0.098	-0.008	0.764	-0.063	0.013	-0.032	0.221
pud*	-0.059	0.000	-0.002	0.944	0.073	0.087	0.060	0.069
ld*	-0.041	0.019	-0.035	0.050	0.018	0.526	-0.043	0.012
diab*	-0.031	0.000	-0.035	0.000	-0.038	0.000	-0.027	0.000
parap*	-0.011	0.404	0.003	0.859	0.000	0.986	0.017	0.379
renaldis*	0.047	0.000	0.045	0.000	0.041	0.000	0.039	0.000
cancer*	0.011	0.001	0.011	0.000	0.007	0.030	0.017	0.000
meta_c~r*	-0.059	0.000	-0.065	0.000	-0.068	0.000	-0.080	0.000
severe~d*	0.010	0.816	0.114	0.073	-0.031	0.423	-0.058	0.027
hiv*	0.065	0.147	-0.063	0.014	-0.051	0.088	-0.088	0.002

* dy/dx is for a discrete change of dummy variable from 0 to 1
^ marginal and average effects are evaluated at the mean of the other regressors

Table 5: Average and marginal effects, emergency inpatients, all years^

	year 0203		year 0304		year 0405		year 0506	
predicted prob	0.102		0.133		0.137		0.128	
variable	dy/dx	P>|z|	dy/dx	P>|z|	dy/dx	P>|z|	dy/dx	P>|z|
lnage	0.050	0.000	0.058	0.000	0.036	0.000	0.042	0.000
seifa	0.000	0.082	0.000	0.409	0.000	0.533	0.000	0.199
severi~1*	-0.043	0.000	-0.082	0.000	-0.079	0.000	-0.070	0.000
severi~3*	0.036	0.000	0.064	0.000	0.052	0.000	0.060	0.000
female*	0.015	0.000	0.018	0.000	0.013	0.000	0.022	0.000
private*	0.008	0.123	0.009	0.077	0.015	0.004	0.017	0.000
multip~y*	0.046	0.000	0.059	0.000	0.057	0.000	0.037	0.000
obese*	-0.028	0.075	-0.051	0.007	-0.036	0.075	-0.038	0.032
weeken~n*	-0.005	0.038	-0.001	0.651	-0.007	0.030	-0.009	0.003
death*	0.010	0.065	0.008	0.213	-0.013	0.051	-0.023	0.000
transep*	-0.007	0.014	-0.018	0.000	-0.016	0.000	-0.032	0.000
numberop	0.024	0.000	0.026	0.000	0.022	0.000	0.028	0.000
ageop	0.000	0.007	0.000	0.012	0.000	0.000	0.000	0.167
agemulti	0.000	0.000	-0.001	0.000	-0.001	0.000	0.000	0.004
ami*	0.086	0.000	0.089	0.000	0.092	0.000	0.071	0.000
chf*	0.020	0.002	0.020	0.014	0.007	0.412	0.015	0.069
pvd*	0.078	0.000	0.062	0.000	0.110	0.000	0.096	0.000
cva*	0.067	0.000	0.121	0.000	0.111	0.000	0.111	0.000
dementia*	0.002	0.932	0.004	0.898	-0.037	0.187	-0.063	0.002
copd*	0.034	0.000	0.069	0.000	0.037	0.004	0.079	0.000
ctd*	0.036	0.346	-0.041	0.234	0.019	0.685	0.073	0.139
pud*	0.069	0.000	0.152	0.000	0.122	0.000	0.173	0.000
ld*	0.046	0.111	-0.002	0.943	0.038	0.259	-0.060	0.001
diab*	-0.029	0.000	-0.042	0.000	-0.031	0.005	-0.013	0.267
parap*	-0.034	0.000	-0.038	0.000	-0.042	0.000	-0.026	0.023
renaldis*	0.035	0.000	0.036	0.000	0.050	0.000	0.041	0.000
cancer*	0.013	0.032	0.013	0.086	0.018	0.023	0.029	0.000
meta_c~r*	-0.059	0.000	-0.087	0.000	-0.091	0.000	-0.096	0.000
severe~d*	-0.022	0.304	-0.008	0.802	-0.010	0.753	0.056	0.214
hiv*	0.042	0.541	0.065	0.491	0.056	0.637	-0.037	0.549

* dy/dx is for a discrete change of dummy variable from 0 to 1
^ marginal and average effects are evaluated at the mean of the other regressors

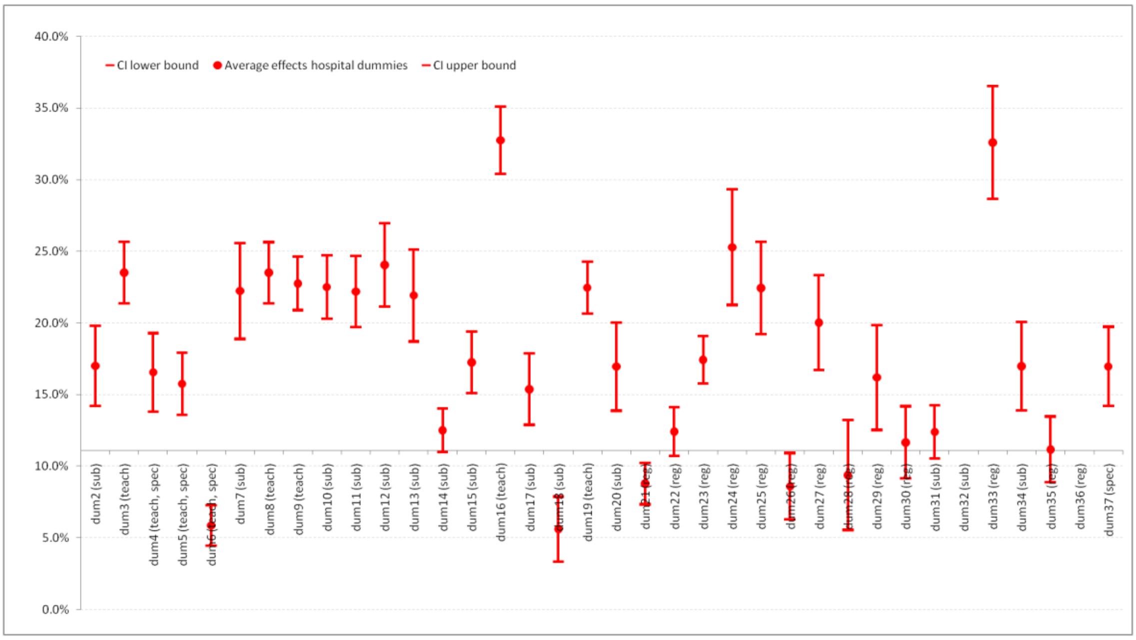

Figure 1: Adverse event rates in Victorian hospitals, elective surgical inpatients, year 2002/03[a] (predicted rate for all hospitals: 11.1%, hospitals 32 and 36 did not report any AEs)

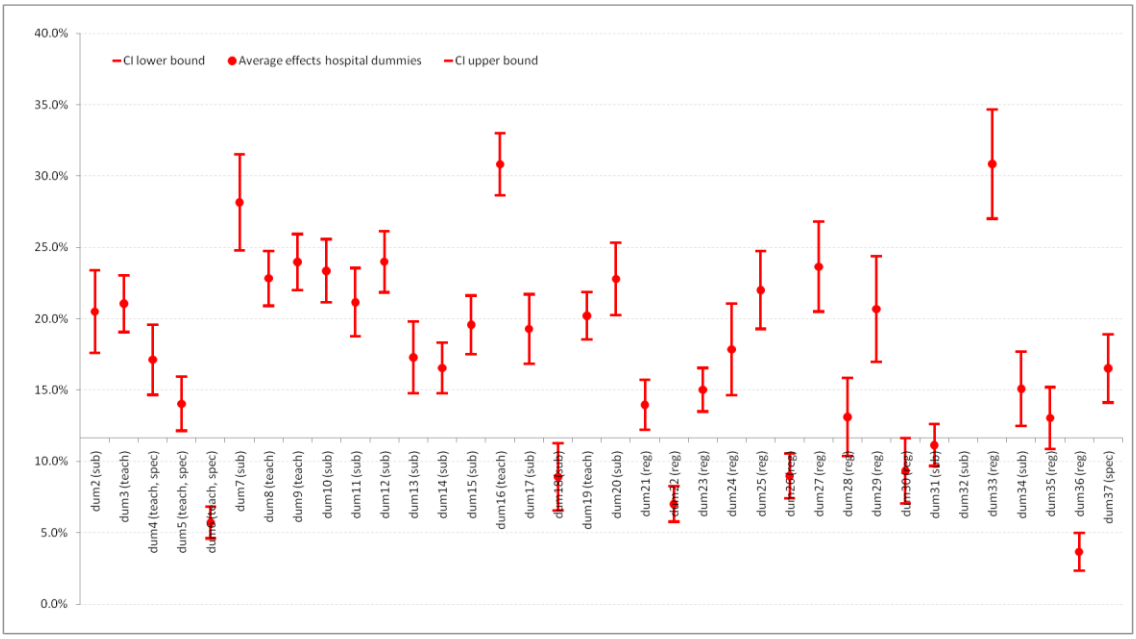

Figure 2: Adverse event rates in Victorian hospitals, elective inpatients, year 2003/04[a] (predicted rate for all hospitals: 11.6%, hospital 32 did not report any AEs

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[a] sub: suburban; teach: teaching; reg: regional, spec: specialty

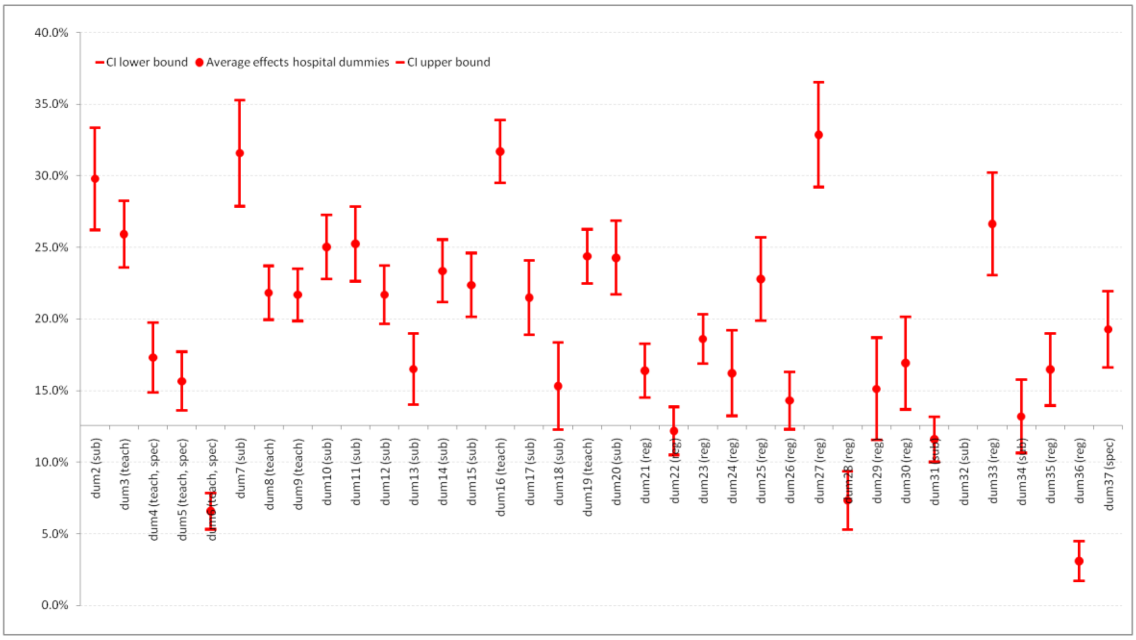

Figure 3: Adverse event rates in Victorian hospitals, elective inpatients, year 2004/05[a] (predicted rate for all hospitals: 12.6%, hospital 32 did not report any AEs)

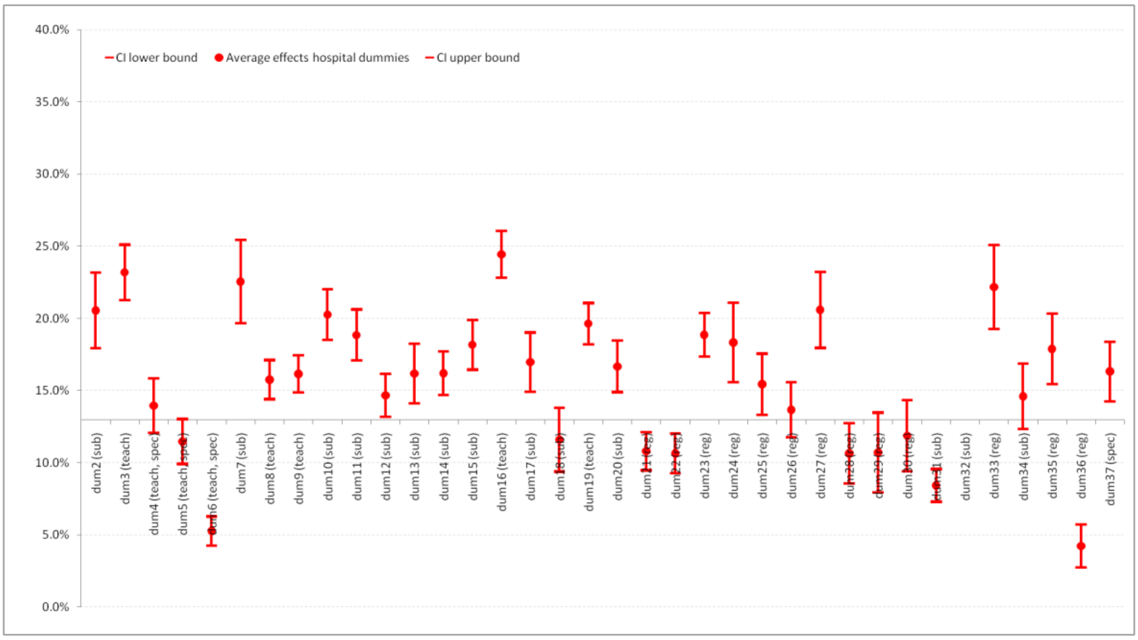

Figure 4: Adverse event rates in Victorian hospitals, elective inpatients, year 2005/06[a] (predicted rate for all hospitals: 13.0%, hospital 32 did not report any AEs)

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[a] sub: suburban; teach: teaching; reg: regional, spec: specialty

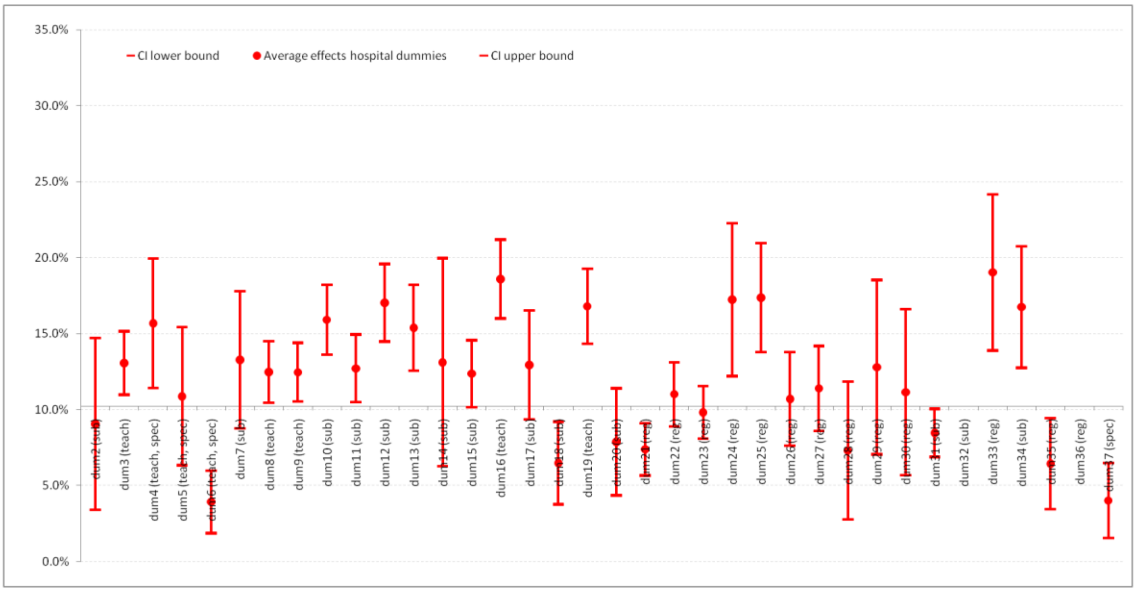

Figure 5: Adverse event rates in Victorian hospitals, emergency inpatients, year 2002/03[a]
(predicted rate for all hospitals: 10.2%, hospital 32 did not report any AEs)

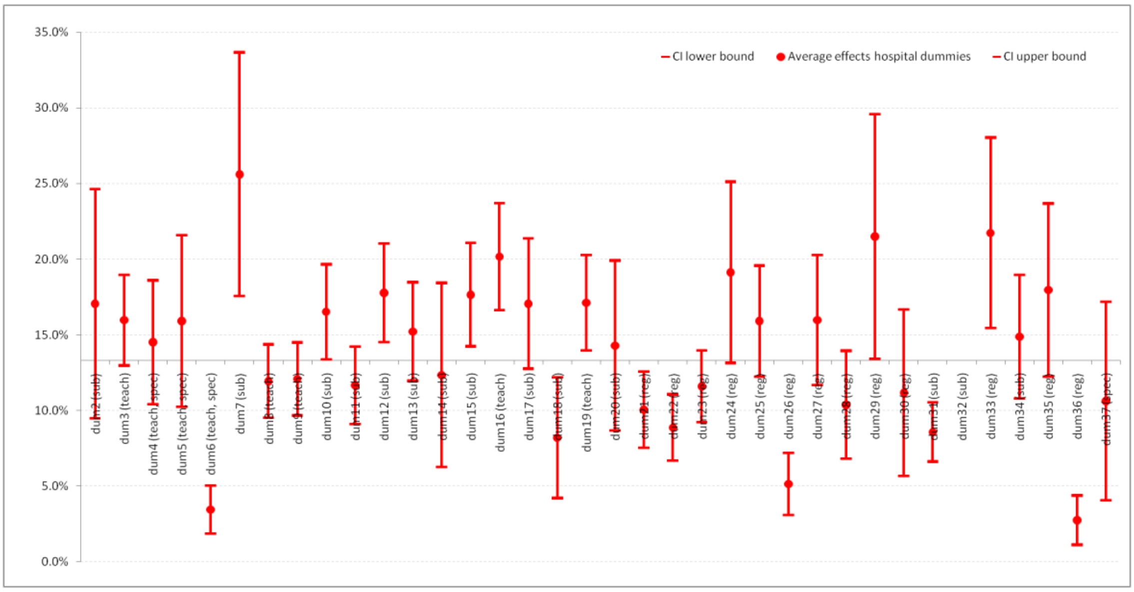

Figure 6: Adverse event rates in Victorian hospitals, emergency inpatients, year 2003/04[a]
(predicted rate for all hospitals: 13.3%, hospital 32 did not report any AEs)

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[a] sub: suburban; teach: teaching; reg: regional, spec: specialty

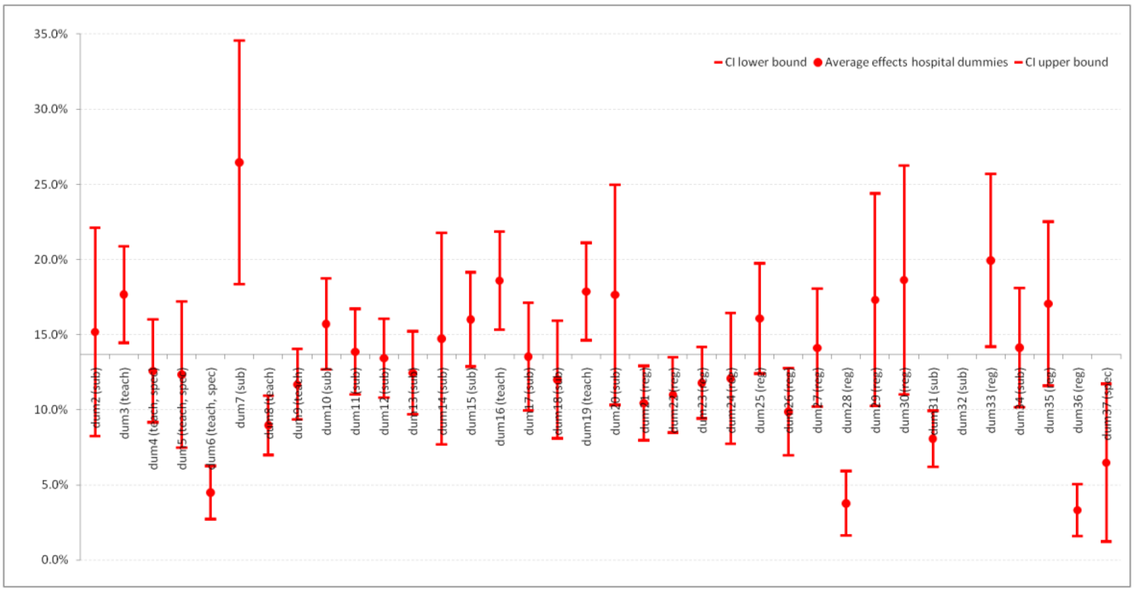

Figure 7: Adverse event rates in Victorian hospitals, emergency inpatients, year 2004/05[a] (predicted rate for all hospitals: 13.7%, hospital 32 did not report any AEs)

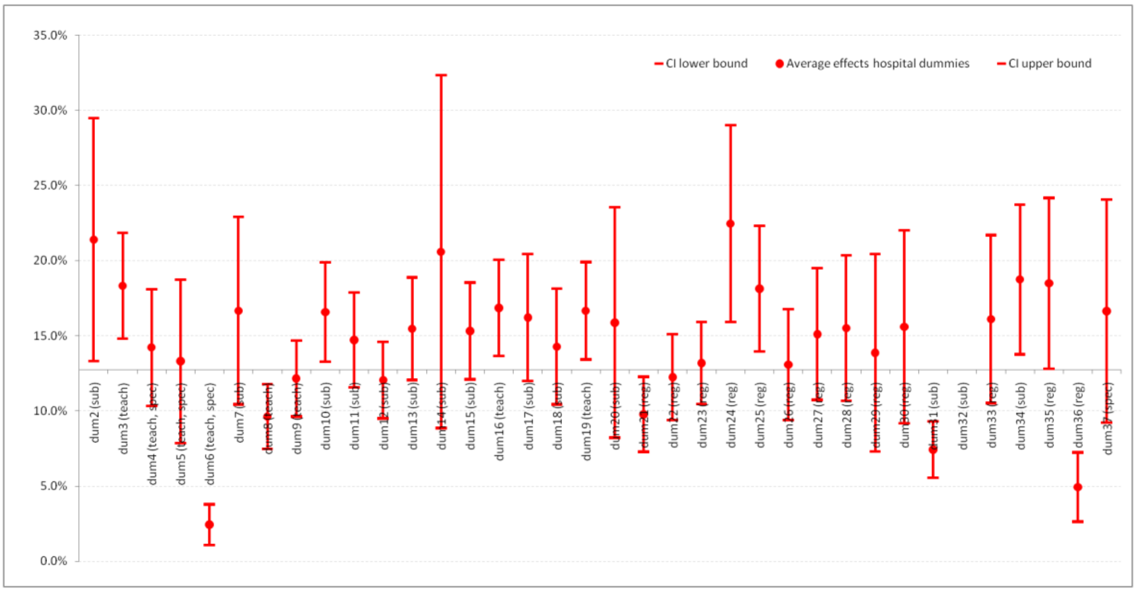

Figure 8: Adverse event rates in Victorian hospitals, emergency inpatients, year 2005/06[a] (predicted rate for all hospitals: 12.8%, hospital 32 did not report any AEs)

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[a] sub: suburban; teach: teaching; reg: regional, spec: specialty

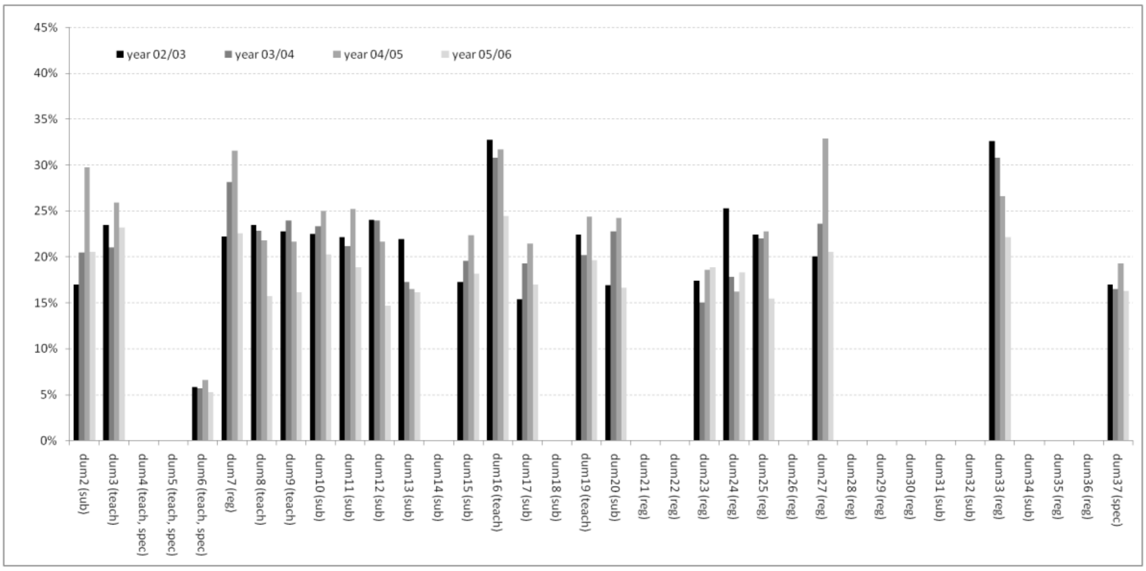

Figure 9: AE rates for elective inpatients in hospitals significantly below or above the predicted rate in all four years[a] (conditional on explanatory factors)

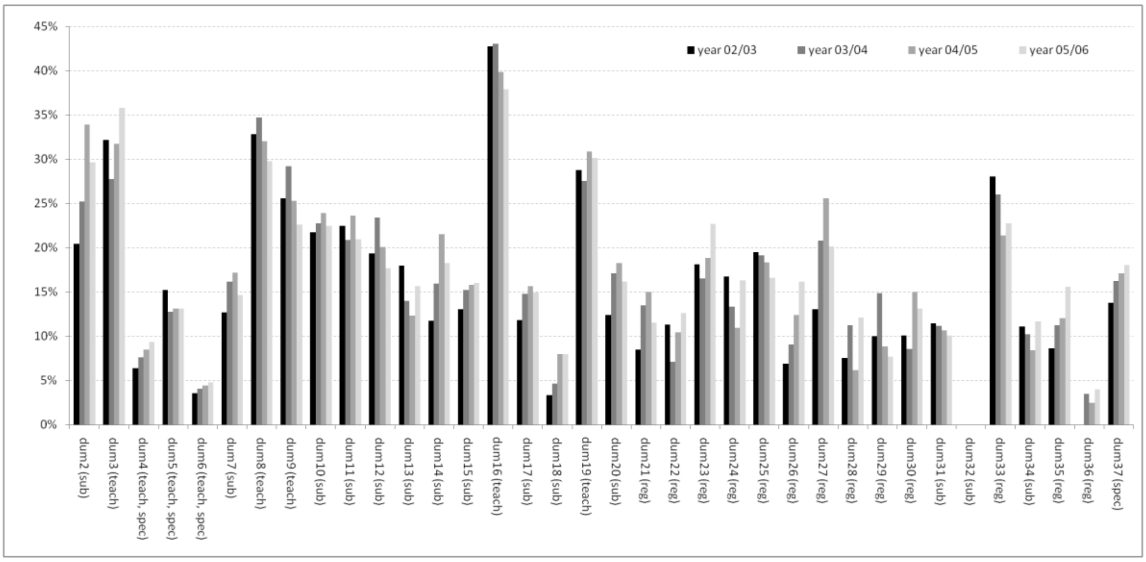

Figure 10: AE rates for elective inpatients in hospitals in all four years[a] (unconditional on explanatory factors)

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[a] sub: suburban; teach: teaching; reg: regional, spec: specialty

References

Arias, Y., D. H. Taylor, et al. (2004). "Association between evening admissions and higher mortality rates in the pediatric intensive care unit." Pediatrics 113(6): 530-4.

Becker, D. J. (2007). "Do hospitals provide lower quality care on weekends?" Health Services Research 42(4): 1589-1612.

Bell, C. M. and D. A. Redelmeier (2001). "Mortality among Patients Admitted to Hospitals on Weekends as Compared with Weekdays." New England Journal of Medicine 345(9): 663-668.

Cameron, A. C. and P. K. Trivedi (2005). Microeconometrics. New York, Cambridge University Press.

Charlson, M. E., P. Pompei, et al. (1987). "A new method of classifying prognostic comorbidity in longitudinal studies: development and validation." Journal of Chronic Disease 40(5): 373-83.

Cram, P., S. L. Hillis, et al. (2004). "Effects of weekend admission and hospital teaching status on in-hospital mortality." American Journal of Medicine 117(3): 151-7.

Dankelman, J. and C. A. Grimbergen (2005). "Systems approach to reduce errors in surgery." Surgical Endoscopy 19(8).

de Vries, E. N., M. A. Ramrattan, et al. (2008). "The incidence and nature of in-hospital adverse events: a systematic review." Quality and Safety in Health Care 17: 216-223.

Department of Health (2005). Victorian additions to the Australian coding standards. Melbourne, State Government of Victoria.

Ehsani, J. P., T. Jackson, et al. (2006). "The incidence and cost of adverse events in Victorian hospitals 2003-04." The Medical Journal of Australia 184(11): 551-555.

Fonarow, G. C., W. T. Abraham, et al. (2008). "Day of admission and clinical outcomes for patients hospitalized for heart failure: Findings from the organized program to initiate lifesaving treatment in hospitalized patients with heart failure." Circulation: Heart Failure(1): 50-57.

Gogel, H. K., M. Liron, et al. (2002). "Mortality among Patients Admitted to Hospitals on Weekends as Compared with Weekdays." New England Journal of Medicine 346(19): 1500-1501.

Hauck, K., N. Rice, et al. (2003). "The influence of health care organizations on health system performance." Journal of Health Services Research & Policy 8(2): 68-74.

Hauck, K. and X. Zhao (2010). A structural equation model of adverse events and length of stay in hospitals. Health Economics Study Group Meeting. London.

Iezzoni, L. I. (2009). "Reinvigorating the Quality Improvement Incentives of Hospital Prospective Payment." Medical Care 47(3): 269-271 10.1097/MLR.0b013e31819c0bce.

Jacobs, R., P. C. Smith, et al. (2006). Measuring Efficiency in Health Care: Analytical Techniques and Health Policy. Cambridge, Cambridge University Press.

Kohn, L. T., J. Corrigan, et al. (2000). To Err is Human: Building a Safer Health System, National Academies Press.

Laudicella, M., K. R. Olsen, et al. (2009). What explains variation in the costs of treating patients in English Obstetrics Specialties? CHE Research Papers, Centre for Health Economics, University of York.

McNair, P., D. Borovnicar, et al. (2009). "Prospective Payment to Encourage System Wide Quality Improvement." Medical Care 47(3): 272-278 10.1097/MLR.0b013e31818b0825.

Olsen, K. R. and A. Street (2008). "The analysis of efficiency among a small number of organisations: how inferences can be improved by exploiting patient-level data." Health Economics 17(671-81).

Schwierz, C., B. Augurzky, et al. (2009). Does the Quality of Hospital Treatment Vary by Days of the Week? Ruhr Economic Papers, Rheinisch-Westfaelisches Institut fuer Wirtschaftsforschung, Ruhr-Universitaet Bochum, Universitaet Dortmund.

Smith, P. C. and A. Street (2006). Concepts and challenges in measuring the performance of health care organizations. The Elgar Companion to Health Economics. A. Jones. Cheltenham, Edward Elgar.

Thomas, E. J., D. M. Studdert, et al. (2000). "Incidence and Types of Adverse Events and Negligent Care in Utah and Colorado." Medical Care 38(3): 261-271.

Wilson, R. M., W. B. Runciman, et al. (1995). "The quality in Australian health care study." The Medical Journal of Australia 163: 458-471.